



Impact of anthropogenic climate change and human activities on environment and ecosystem services in arid regions

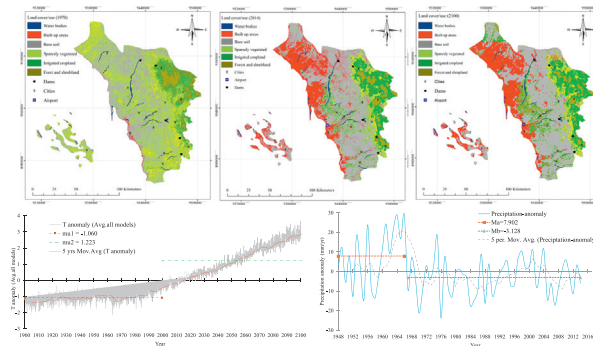
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HIGHLIGHTS

- Use of EO data to drive land use categories between 1970 and 2014
- Markov-CA to detect land use change pattern in the area
- Human activities and land use change and their impacts on climate and environment.
- Anthropogenic climate change detection and trend between 1900 and 2010
- Projections of land use trend between 1900 and 2010 and its potential anthropogenic climate change

GRAPHICAL ABSTRACT



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ABSTRACT

The implications of anthropogenic climate change, human activities and land use change (LUC) on the environment and ecosystem services in the coastal regions of Saudi Arabia were analyzed. Earth observations data was used to drive land use categories between 1970 and 2014. Next, a Markov-CA model was developed to characterize the dynamic of LUC between 2014 and 2100 and their impacts on regions' climate and environment. Non-parametric change point and trend detection algorithms were applied to temperature, precipitation and greenhouse gases data to investigate the presence of anthropogenic climate change. Lastly, climate models were used to project future climate change between 2014 and 2100. The analysis of LUC revealed that between 1970 and 2014, built up areas experienced the greatest growth during the study period, leading to a significant monotonic trend. Urban areas increased by 2349.61 km² between 1970 and 2014, an average increase of >53.4 km²/yr. The projected LUC between 2014 and 2100 indicate a continued increase in urban areas and irrigated cropland. Human alteration of land use from natural vegetation and forests to other uses after 1970, resulted in a loss, degradation, and fragmentation, all of which usually have devastating effects on the biodiversity of the region. Resulting in a statistically significant change point in temperature anomaly after 1968 with a warming trend of 0.24 °C/decade and a downward trend in precipitation anomaly of 12.2 mm/decade. Total greenhouse gas emissions including all anthropogenic sources showed a statistically significant positive trend of 78,090 Kt/decade after 1991. This is reflected in the future projection of temperature anomaly between 1900 and 2100 with a future warming trend of 0.19 °C/decade. In conclusion, human activities, industrial revelation, deforestation, land use transformation and increase in greenhouse gases had significant implications on the environment and ecosystem services of the study area.

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1. Introduction

Some countries have suffered from significant impact of climate change, such as rising sea level, extreme weather events and changing hydrological cycle. However, human activities could also incur severe negative effects on our environment which in turn affect our livelihood worldwide. There have been studies on how land use change (LUC) and climate change have affected the ecosystems and the environment at various spatiotemporal scales (Perrings et al., 2011; Tong et al., 2012; Reeves et al., 2018). In this study, we assess how have LUC patterns and climate change impacted the environment and ecosystem services of coastal regions of Arabia. In recent years, studies show that human activities, including LUC and deforestation, have resulted in major global environmental change and impacts (Verburg et al., 2011; Sirami et al., 2017; Prestele et al., 2017). In Saudi Arabia, for instance, the impact of human exploitation of water resources is obvious in the Layla Aflaj lakes and deep waterholes of the Al-Kharj region. Since 1980s, excessive water consumption due to agriculture activities and domestic purposes have significantly depleted these resources (Schleusener et al., 2013). Sadly, valuable water sources from limited number of natural lakes in Arabia formed by groundwater aquifers over many centuries are now the region's history. In the past, the region was characterized by heavy rainfall and was large occupied by shrubland and forests (Thouless et al., 1991). However, human activities and land use change had further decreased the already scarce water resources of this region, and similarly in other parts of the Arabian Peninsula. To mitigate the impact of severe droughts, growing population, and food security, multiple rainwater harvesting dams were constructed in high mountains to collect rainwater for all purposes, forestlands were replaced by agriculture fields and wild animals were hunted for food.

Human and climate change impacts on the arid environment are generally not well documented, even though such information will help us to better understand how these human activities will affect natural resources in the arid environment, and what conservation plans would be helpful. In recent decades, many LUC studies have been conducted (Shalaby and Tateishi, 2007; Wang et al., 2009; Woldesenbet et al., 2017), of which some have considered extensive LUC as the main drivers to biodiversity loss, fragmentation, habitat reduction, and food security (Wilson and Weng, 2011; Nasta et al., 2017; Liang et al., 2017; Fu et al., 2017). It seems uncurbed human exploitation of natural resources could irreversibly impact the future of mankind in centuries to come. From remotely sensed data acquired by earth observation satellites, it is now possible to use a geographic information system to derive various LUC patterns, trends and magnitude of high temporal and spatial resolutions (Lu et al., 2004; Long et al., 2007; Shalaby and Tateishi, 2007).

Various change detection methods have been employed in LUC studies, such as the principal component analysis (PCA), band differencing, band ratioing, neural network, support vector machine, and post-classification techniques (Ridd and Liu, 1998; Lu et al., 2004; Petrosillo et al., 2013). However, the Markov Chains method has dominated many LUC studies (Pontius and Malanson, 2005). Researchers often combine this method with Cellular Automata (CA) to control the decision-making process and to enhance the ability to change/add or even modify factors that drives LUC in form of transition rules (Longley and Batty, 1996; Clarke and Gaydos, 1998; Zhang et al., 2009). Cellular Automata has been successfully utilized to project future LUC (Myint and Wang, 2006; Marshall and Randhir, 2008; Guan et al., 2011; Huishi et al., 2012; Huang et al., 2014). By combining these two methods to a LUC study conducted in Norman, Oklahoma, USA, Myint and Wang (2006) achieved an accuracy of 86% which is of acceptable accuracy (Anderson et al., 1976; Townshend, 1981). Similar accuracy was obtained by Marshall and Randhir (2008) to assess future land cover based on transition rules of Markov-CA. More recently, Guan et al. (2011) and Huishi et al. (2012) found that a combination of Markov-CA is more accurate than other LUC models.

Past studies suggest that LUC patterns would affect local temperature and precipitation (e.g., Pielke et al., 2007). Weng (2001) concluded that rapid urbanization led to climate warming because of increasing CO₂ emissions. Moreover, Pielke (2005) showed that rising concentration of greenhouse gases in the atmosphere is the best-known impact of human activities on climate change and LUC. Pettit's test and Mann-Kendall test have been widely used to detect changes in climate data. Pettit's test (Pettit, 1979) is a popular non-parametric approach for detecting change points in the time series of climate variables (Ma et al., 2008; Mahé and Paturel, 2009; Martínez et al., 2010). The non-parametric Mann-Kendall (Sneyers, 1992) test is widely used to estimate trends in climate data and whether the trend is statistically significant (Zhang et al., 2000; Yue et al., 2002; Dawood, 2017).

We investigated the impacts of anthropogenic climate change and LUC caused by human activities on the environment and ecosystem services of the study sites. To achieve our objectives, we used earth observations data (EO) of satellites to derive land use categories at different spatial and temporal scales in the Jizzan Province-Arabia for 1970–2014. Then, using the Markov-CA approach, the temporal/spatial dynamics of LUC patterns in the study area for 2014–2100 were derived and their impacts on the climate, environment, and water resources were analyzed. Pettit's and Mann-Kendall tests were applied on temperature data over 1900–2010, and precipitation data over 1948–2014 to detect change points and to estimate trends in the region. The impact of global warming due to increasing greenhouse gases were also analyzed between 1960 and 2015. Lastly, future effects of LUC and climate change in the study area, were analyzed using RCP4.5, RCP6.0 and RCP8.5 climate change scenarios projected by climate models of CMIP5 and IPSL-CM5A-LR between 2014 and 2100. Without any major river, the water resources of Saudi Arabia depend heavily on precipitation and groundwater sources. Given evapotranspiration (ET) plays a major role in its climate and the fauna and flora of its desert environment, we have also estimated the potential ET of the study area over 1950–2016 and projected possible changes over 2016–2100.

2. Data and research methods

2.1. Study area and data sets

As the Jizzan Province (Fig. 1) lies on the coastal regions of Arabia (16°53'21"N 42°33'40"E), it has a different climate than the rest of Arabia. In the past Jizzan was dominated by forest, shrubland and different species of wild animals. The province also includes >100 islands in the Red Sea that in the past were rich in animals and biodiversity. Landsat cloud-free images for Jizzan in 1970, 1980, 1990, 2000, 2010, and 2014 were obtained from the King Abdulaziz City for Science and Technology (KACST) (Table 1). Monthly precipitation data between 1948 and 2014 and temperature data between 1900 and 2010 were derived from the 20th Century Reanalysis V2 Dataset. CO₂ and other greenhouse gas emissions data were obtained from the Carbon Dioxide Analysis Center of Environmental Sciences Division, USA.

2.2. Land use classification and accuracy assessment

Landsat images were preprocessed, made as mosaic, and geometrically corrected based on a rectified SPOT-5 "2.5m PSM" satellite image for the Jizzan province. This image also served as the reference image for land use classification and accuracy assessment. Then, these images were also atmospherically corrected by normalizing these images to the SPOT-5 image. Lastly, the Landsat images have been radiometrically normalized to the reference image based on manually identified 16 pseudo-invariant features (PIFs). Two field surveys were set up, the first was before land use classification to collect ground control points (GCP). Five hundred GCP were collected in the first trip for land use classification, which was performed using these GCP and visual

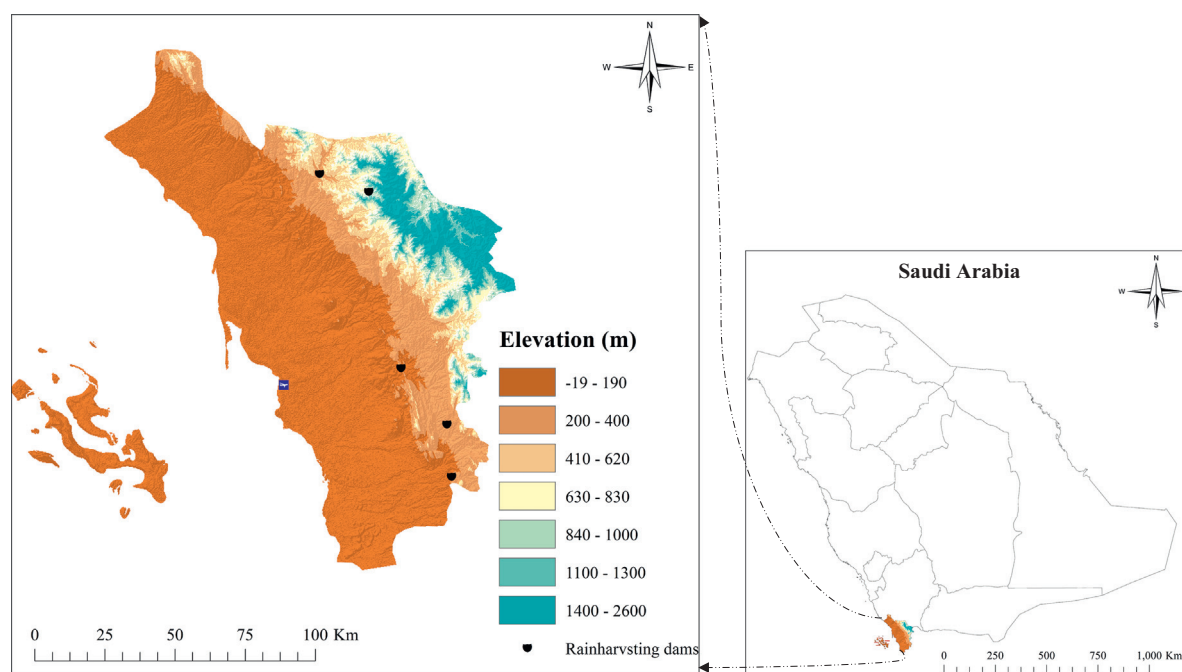


Fig. 1. Location map of Jizzan Province, Kingdom of Saudi Arabia.

interpretations of Google Earth images. In the second trip, we collected 100 points for validating the classified images.

The popular, Iso Cluster Unsupervised and Maximum Likelihood Classification was applied to the Landsat images, to classify the land use/cover (Baker et al., 2006; Panda et al., 2009; Mukherjee et al., 2010; Jiménez-Bello et al., 2012). Six land use/cover classes were identified in each land use map: water bodies, built-up areas, bare soil, sparse vegetation, irrigated cropland, forest and shrubland. The accuracy of these maps was assessed using both simple random and stratified random patterns. Further, a questionnaire consists of two types of questions was prepared to ask residents about anthropogenic effects on the region. The first type consists of preliminary questions such as areas of cultivated lands, and number of groundwater wells used to irrigate crops. The second type of questions consist of three tables, which include affirmative statements about social and environmental impacts of oil discovery, climate change and human activities in the study area. The questionnaire was set up under a five-point scale (strongly agree, agree, not sure, disagree, strongly disagree) to allow farmers to choose the extent of their agreement or disagreement to each statement.

2.3. Changes and dynamics of land use/cover

The areal distribution of each land use class was estimated for all time periods to determine the dynamics and patterns of land use/cover change (LUC). LUC and trends were estimated in terms of gain, loss and net change for each temporal period by class. LUC drivers

were then identified based on the Markov Chains transition probabilities. A coupled Markov-CA model was used to project changes and the future spatial distribution of LUC. From the results, we derive the transition probability matrix which represents the probability of each land use class to change to another class or to remain unchanged in the next time period. Next, transition area matrices were developed to estimate the total area expected to change at each period. Finally, based on the historical LUC in the area, conditional probability images, one for each land use/cover class was developed to show the likelihood of each class will change to other classes or not. Five historical transition matrices were constructed from the cross-tabulation of the land use/cover maps between 1970, 1980, 1990, 2000, 2010, and 2014. The time interval between the transition matrices was 10 years. The approach of Pastor et al. (1993) was adopted to transform transition probabilities to annual time steps to consider the differences in the lengths of the last period (2010–2014) (Table 3). Major drivers of land use dynamics in the study area for each study period were identified. As expected, urbanization and agriculture activities at the expenses of forestland and shrubland were the major drivers for LUC.

To project future LUC in the study area, we first tested the model's ability to simulate historical LUC based on the annualized transition matrices. Transition probabilities for future LUC are developed from trends observed in the past, e.g., the land use in 2010 was simulated on the basis of the 1990 and 2000 transition matrices. Various studies have adopted this approach (Araya and Cabral, 2010; Yang et al., 2014; Singh et al., 2015; Keshtkar and Voigt, 2016; Han and Jia, 2017). For instance, Araya and Cabral (2010) compared the actual land use map in 2010 derived from EO data with that simulated for 2010 based on LUC between 1990 and 2000. Similarly, Singh et al. (2015) used actual transition probabilities between 2000 and 2010 to project LUC in 2020. In this study, we used the transition probability between 1970 and 1980 to simulate LUC in 1990. Similarly, the 2000 land use map was simulated from the 1980–1990 transition matrix. Finally, the land use map of 2010 and 2014 were simulated based on transition probability matrices of 1990–2000 and 2000–2010, respectively.

The main limitation of the Markov-CA model is that it assumes factors of past changes remain the same in the future. However, using multiple actual land use maps as an accuracy assessment, high accuracies of projection could be obtained (Yagoub and Al Bizreh, 2014; Guan et al.,

Table 1
Earth observation data used in this study.

Images Used for the study	Resolution (m)	Date of acquisition	Format	Product Type (Cloud Cover %)
Landsat 1–5 MSS	30	06/03/1970	GEOTIFF	L1T (0%)
Landsat 1–5 MSS	30	01/09/1980	GEOTIFF	L1T (0%)
Landsat 5 TM "Band 1–7"	30	24/02/1990	GEOTIFF	L1T (0%)
Landsat 7 ETM+ "Band 1–8"	30	04/01/2000	GEOTIFF	L1T (0%)
SPOT-5 "PSM"	2.5	06/03/2000	GEOTIFF	L1T (0%)
Landsat 7 ETM+	30	05/01/2010	GEOTIFF	L1T (0%)
Landsat 8	30	03/04/2014	GEOTIFF	L1T (0%)

2011). Guan et al. (2011) used the transition probability matrix of 1997–2006 to project LUC for 2024, which then was set as the starting year to project LUC for 2033, but again based on the transition probability matrix of 1997–2006, and 2033 as the starting year to project the 2042 LUC. In our study, we followed this approach and applied the Kappa Index of Agreement (KIA) to validate the model performance by comparing the simulated land use map at each year against the actual land maps. KIA was also used to test for spatial and quantitative agreement between every two maps. Table 2 shows how well the land use maps were classified. The overall accuracy of the land use maps for 1970, 1980, 1990, 2000, 2010, and 2014 was assessed to be 80.52%, 84.33%, 85.17%, 84.9%, 87.2%, and 94.8% respectively. KAPPA indices for these maps estimated at 0.76, 0.755, 0.717, 0.82, 0.85, and 0.89, respectively are all of acceptable accuracy. Next, the Markov–CA model was used to project the future LUC and land use map at 2025 based on the transition probability of 2010–2014, taking 2014 as the starting point. Then land use map at 2050 was simulated based on the same transition probability matrix but taking 2025 as the starting point. Finally, land use map at 2075 and 2100 was simulated taking 2050 and 2075 as the starting point respectively.

3. Anthropogenic climate change detection

Land-use change is a major player to climate change since it contributes to atmospheric CO₂ emission (Dale et al., 2011). Therefore, we also analyzed CO₂ and other greenhouse gases emissions and their by-product: hydrofluorocarbons (HFC), perfluorocarbons (PFC), sulfur hexafluoride (SF₆), all anthropogenic CH₄ and N₂O sources in thousand metric tons (Kt) of CO₂ equivalent. Change point and trend detections were applied to these data to detect climate change in the study area which might be attributed to LUC and increased global warming as suggested by Dale et al. (2011) and Searchinger et al. (2008). For the Jizzan province, we analyzed the variability of long-term monthly precipitation and temperature anomalies from the long-term mean precipitation of 1948 to 2016, and long-term mean temperature of 1900–2010, respectively. To detect trends and change points, we used nonparametric, Pettitt and Mann–Kendall tests (MK) on the time series of temperature, temperature anomaly, precipitation, precipitation anomaly, respectively. Change points were calculated as follows (Pettitt, 1979):

$$K_T = \max[U_T, T] \quad (1)$$

where,

$$U_T, T = \sum_{i=1}^{n-1} \sum_{j=t+1}^n \text{sgn}(x_j - x_i) \quad (2)$$

The change-point of the series is located at K_T , provided that the statistic is significant. The significance probability of K_T is approximated for

$p \leq 0.05$ with

$$p \approx 2e^{-6K_T^2 / (T^3 + T^2)} \quad (3)$$

The Mann–Kendall test was applied to estimate trends of climate data as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (4)$$

Trend is estimated for a time series $x_i, i = 1, 2, \dots, n-1$ and $x_{j,j} = i + 1, i + 2, \dots, n$. Each x_i is reference and compared with remaining data points x_j (see 2):

$$\text{Sgn}(x_j - x_i) = \begin{cases} +1 & \text{if } (x_j - x_i) > 0 \\ 0 & \text{if } (x_j - x_i) = 0 \\ -1 & \text{if } (x_j - x_i) < 0 \end{cases} \quad (5)$$

The variance statistic is calculated as follow:

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{j=1}^p t_j(t_j-1)(2t_j+5)}{18} \quad (6)$$

where p is the number of groups in which each group consists of data points of equal values, and t_j is the number of data points in the j_{th} group. Using the following Z-transformation, S is approximately normally distributed:

$$Z = \begin{cases} \frac{S-1}{(\text{Var}(S))^{0.5}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{(\text{Var}(S))^{0.5}} & \text{if } S < 0 \end{cases} \quad (7)$$

The slope (T_j) is computed according to Sen (1968) as follow:

$$T_j = \frac{x_j - x_i}{j - i} \quad (8)$$

The magnitude of the trend is obtained from the slope estimator method (Sen, 1968). The sign of the slope indicates if the trend of the time series is positive or negative.

Climate change scenarios of RCP4.5, RCP6.0 and RCP8.5 projected by climate models of CMIP5 and IPSL-CM5A-LR between 2014 and 2100 were used to project future warming in the study area. Future climate projections of these climate models were analyzed separately and then averaged for the study area. Statistical downscaling techniques of Frias et al. (2006) and Guo et al. (2014) based on empirical relationships between climate models' output and local weather information were used to downscale climate models' projections to local-scale. Again, the Pettitt's test and Mann–Kendall approach were used to detect change points and trends of climate projections that have been downscaled

Table 2
Accuracy assessment and validation of land use-land cover maps.

LULC	1970			1980			1990			2000			2010			2014		
	UA (%)	PA (%)	Kappa	UA (%)	PA (%)	Kappa	UA (%)	PA (%)	Kappa	UA (%)	PA (%)	Kappa	UA (%)	PA (%)	Kappa	UA (%)	PA (%)	Kappa
Water bodies	80.2	79	0.72	78.12	76.5	0.71	86.8	77.6	0.69	89.1	90.9	0.82	79.61	70.4	0.88	93.21	94.6	0.86
Built up areas	79.9	82.2	0.81	92.62	90.4	0.82	90.35	89.8	0.77	90.2	85.62	0.86	94.58	92.8	0.98	96.85	94.36	1
Bare soil	84.2	84.8	0.62	88.22	78.2	0.71	88.12	85	0.67	79.6	75.43	0.83	88.5	84.64	0.78	95.47	93.85	0.79
Sparsely vegetated	81.5	77.51	0.7	79.32	80.3	0.68	75.41	80.2	0.735	81.3	91.5	0.9	91.7	79.3	0.76	94.65	96.92	0.84
Irrigated cropland	76.2	78.52	0.86	83.44	84.35	0.76	87.35	90.24	0.725	88.29	89	0.78	86.55	90.4	0.845	92.69	94.54	0.89
Forest and shrubland	78.9	83.3	0.87	91.1	89.4	0.85	84.9	86.23	0.71	79.5	78.41	0.75	93.32	94.6	0.86	93.74	96.77	0.94
OA	80.519		0.76	84.33		0.755	85.17		0.717	84.90		0.82	87.20		0.85	94.80		0.89

UA, user's accuracy; PA, producer's accuracy; OA, overall accuracy.

Table 3

Land use transitions probabilities 1970–2014.

1970–1980 Markov matrix ^a							
Code	Land cover/use class	Water bodies	Built up areas	Bare soil	Sparsely vegetated	Irrigated cropland	Forest and shrubland
1	Water bodies	0	0.0491	0.0844	0.0055	0.0009	0.0005
2	Built up areas	0.8597	0.1496	0.7078	0.0213	0.0014	0.0005
3	Bare soil	0.1194	0.0177	0.8893	0.082	0.0044	0.0027
4	Sparsely vegetated	0.004	0.0032	0.7375	0.2412	0.0124	0.0049
5	Irrigated cropland	0.0007	0.0007	0.203	0.6457	0.1185	0.0318
6	Forest and shrubland	0.0005	0.0003	0.0672	0.4327	0.267	0.2328
1980–1990 Markov matrix ^a							
Code	Land cover/use class	Water bodies	Built up areas	Bare soil	Sparsely vegetated	Irrigated cropland	Forest and shrubland
1	Water bodies	0.9231	0.0461	0.0285	0.0013	0.0006	0.0003
2	Built up areas	0.1102	0.2392	0.6506	0	0	0
3	Bare soil	0.0012	0.0167	0.9072	0.07	0.003	0.002
4	Sparsely vegetated	0	0	0.6487	0.3317	0.0147	0.0049
5	Irrigated cropland	0.0005	0	0	0.7752	0.1881	0.0362
6	Forest and shrubland	0.0002	0.0004	0	0.3282	0.3078	0.3633
1990–2000 Markov matrix ^a							
Code	Land cover/use class	Water bodies	Built up areas	Bare soil	Sparsely vegetated	Irrigated cropland	Forest and shrubland
1	Water bodies	0.7992	0.0527	0.137	0.0093	0.0012	0.0006
2	Built up areas	0.1278	0.053	0.7584	0.0562	0.0029	0.0017
3	Bare soil	0.0067	0.0188	0.871	0.0944	0.0058	0.0033
4	Sparsely vegetated	0.0018	0.0118	0.8261	0.1452	0.0101	0.005
5	Irrigated cropland	0.0005	0.0001	0.5817	0.3526	0.0449	0.0203
6	Forest and shrubland	0.0002	0	0.2593	0.4946	0.1474	0.0986
2000–2010 Markov matrix ^a							
Code	Land cover/use class	Water bodies	Built up areas	Bare soil	Sparsely vegetated	Irrigated cropland	Forest and shrubland
1	Water bodies	0.6152	0.0766	0.248	0.0271	0.0238	0.0093
2	Built up areas	0.0399	0.5438	0.3791	0.0169	0.0164	0.0039
3	Bare soil	0	0.1069	0.798	0.0577	0.0281	0.0083
4	Sparsely vegetated	0.0001	0.0087	0.5982	0.2039	0.1613	0.0277
5	Irrigated cropland	0	0.0032	0.3339	0.2021	0.3278	0.1329
6	Forest and shrubland	0	0.0017	0.0807	0.0817	0.3756	0.4604
2010–2014 Markov matrix ^a							
Code	Land cover/use class	Water bodies	Built up areas	Bare soil	Sparsely vegetated	Irrigated cropland	Forest and shrubland
1	Water bodies	0.4735	0.1019	0.342	0.0369	0.0325	0.0132
2	Built up areas	0.0477	0.4051	0.4871	0.0303	0.0231	0.0068
3	Bare soil	0.0031	0.1354	0.7455	0.0644	0.04	0.0125
4	Sparsely vegetated	0	0.0446	0.6555	0.1279	0.1282	0.0438
5	Irrigated cropland	0	0.0177	0.4592	0.1584	0.2358	0.1289
6	Forest and shrubland	0.002	0.0005	0.1767	0.1347	0.3598	0.3283

^a Values are probabilities of transition.

statistically. Given evapotranspiration (ET) plays a major role in the climate of a desert environment, the increase in ET has been linked to rising atmospheric CO₂ concentration and climate warming (Kang et al., 1999; Abteu and Melesse, 2013). We estimated the potential ET of the study area over 1950–2016 and projected possible changes over 2016–2100 of the study area using Penman Monteith's method (Allen et al., 1998). Precipitation surplus (precipitation - PET), which represents the hydro-logic impact of climate change in the region, was also estimated.

4. Discussion of results

4.1. Impact of land use dynamics on environment

Impacts of climate change and human activities to the study area have not been documented even though environmental changes such

as plant distributions have been going on for years. We have analyzed results of a survey based on questionnaire we developed with local farmers about possible environmental and social impacts of climate change and LUC on the study area. The local residence's responses strongly advocated the high social and environmental costs associated with human activities such as mining of oil, LUC, and dams in the region are: loss of biodiversity and fertile soil, air and water pollution, degradation of farmland, damage to aquatic ecosystem, increased desertification and a decline in vegetative cover. Results of the analysis presented in Fig. 2a and b reveal a large expansion in urban areas after 1970s, and a decline in irrigated cropland, forest, shrubland, and sparse vegetation cover during 1970s and 1980s, respectively. During this period, many farmers left their agricultural land and migrated to cities for jobs, which led to a decline in vegetative cover and lumbering for industrial uses. The construction of five dams in 1970, 1998 and 2000 to store

Table 4

Area measurements of land-cover/use within Jizzan province for each subperiod and the full period 1970–2014.

		1970		1980		1990		2000		2010		2014	
Code	Land cover/use class	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)
1	Water bodies	70.470	0.535	100.918	0.766	86.573	0.657	84.677	0.642	78.027	0.592	73.362	0.557
2	Built up areas	106.820	0.810	139.392	1.057	532.915	4.043	1399.518	10.617	2223.766	16.870	2456.430	18.635
3	Bare soil	5776.400	43.820	9395.668	71.276	10,147.186	76.981	9608.147	72.891	7593.928	57.611	7020.124	53.256
4	Sparsely vegetated	5290.940	40.137	2817.407	21.373	1842.248	13.976	1085.457	8.235	1129.829	8.571	1120.279	8.499
5	Irrigated cropland	1065.295	8.081	450.4329	3.417	549.1719	4.166	781.9578	5.932	1792.368	13.598	1963.683	14.897
6	Forest and shrubland	872.1918	6.616	278.3241	2.111	23.4	0.178	221.7375	1.682	363.5766	2.758	548.0865	4.158

Table 5

Detected land cover/use gains and losses within Jizzan province for each subperiod and the full period 1970–2014.

Code	Land cover/use class	1970–1980		1980–1990		1990–2000		2000–2010		2010–2014	
		Change (Km ²)	Change (%)	Change (Km ²)	Change (%)	Change (Km ²)	Change (%)	Change (Km ²)	Change (%)	Change (Km ²)	Change (%)
1	Water bodies	−30.45	−0.23	14.35	0.11	1.90	0.01	6.65	0.05	4.67	5.98
2	Built up areas	−32.57	−0.25	−393.52	−2.99	−866.60	−6.57	−824.25	−6.25	−232.66	−10.46
3	Bare soil	−3619.27	−27.46	−751.52	−5.70	539.04	4.09	2014.22	15.28	573.80	7.56
4	Sparsely vegetated	2473.53	18.76	975.16	7.40	756.79	5.74	−44.37	−0.34	9.55	0.85
5	Irrigated cropland	614.86	4.66	−98.74	−0.75	−232.79	−1.77	−1010.41	−7.67	−171.32	−9.56
6	Forest and shrubland	593.87	4.51	254.92	1.93	−198.34	−1.50	−141.84	−1.08	−184.51	−50.75

Where (−) gain, (+) loss.

rainwater for agriculture activities and domestic purposes affected the biodiversity of the region, and significantly increased the LUC. The extent of LUC distribution over the study period (1970–2014) is presented in Table 4. Urbanized areas increased from 106.82 km² (0.81% of total area) in 1970 to 139.39 km² (1%) in 1980, a 25% increase in 10 years, while sparsely vegetated land declined dramatically from 5290.94 km² (40%) in 1970 to 2817.407 km² (21%) in 1980.

There was an increase in areas of water bodies from 70.47 km² (0.5% of the total area) in 1970 to 100.90 km² (0.8%) in 1980 due to the construction of rainwater retention facilities, which helped farmers to recover loss of agricultural land in later years. From 1980 to 1990, areas of bare soil increased from 9395.7 km² to 10,147.2 km², urbanized areas increased from 1.057% to 4% of the total area, but areas of forest and shrubland significantly decreased from 278.3 km² to 23.4 km², which fortunately was restored to 221.7 km² due to conservation efforts implemented in 2000. Sparse vegetative cover continued to decline, losing >975.0 km² of its 1980 area to 1842.2 km² in 1990 and to 1085.4 km² in 2000, which marginally increased between 2010 and 2014 to 1120.0 km² in 2014. Relative to 1980, irrigated cropland increased significantly from 450.4 km² in 1980 to 1963.7 km² over the 1990–2014 period. Table 5 shows LULCC (%) in the study area for each subperiod and the 1970–2014 period. Spatial patterns of LUCs in the Jizzan Province for 1970, 1980, 1990, 2000, 2010, and 2014 given in Fig. 2 show that bare soil and sparse vegetative cover were dominant, but over the years urbanization expanded in the coastal regions. From 1990 to 2014, urbanized areas replaced most of the water bodies and extended into coastal areas, and consequently areas of bare soil and water bodies declined markedly. The rate of urban expansion since 1970s was >53.4 km² yr^{−1}.

LUC had significantly affected forest, shrubland and vegetation covers, which in turn might have affected ecosystems, natural habitat and biodiversity of the region. Human alteration of land use from natural vegetation and forests to other land uses typically results in a loss, degradation, and fragmentation of ecosystems, which tend to have negative effects on the biodiversity of the region, as also reported by local residents impacts over the years. Because of depleted groundwater resources, rainwater harvesting dams were constructed which substantially captured the surface water. The regional change in hydrology due to human activities resulted in the loss of forest covers, altered landscape patterns and ecosystem of the region.

4.2. Anthropogenic climate change and human activities

We applied Pettitt's test to detect anthropogenic change points of the region, which reveals statistically significant change points in monthly temperature and temperature anomaly in 1968. The mean temperature anomaly increased significantly from −0.206 °C between 1900 and 1968 (Mb: average before the change point) to 0.326 °C (Ma: average after the change point) between 1968 and 2010 (Table 6). The Mann-Kendall trend test also show a statistically significant warming trend of 0.24 °C per decade since 1968, which reflects the impact of anthropogenic climate change and LUC such as decline in forest, shrubland, and sparsely vegetated land since 1970 (Fig. 3) due to agricultural development which reached its zenith in 2000s.

Similarly, from Pettitt's test applied to monthly precipitation anomaly data for 1948–2014, a statistically significant change point was detected in 1967, as the mean precipitation anomaly declined from 7.9 mm/yr (Mb = 7.9 mm/yr) between 1948 and 1967 to −3.12 mm/yr (Ma = −3.12 mm/yr) between 1967 and 2010 (Fig. 4). Trend analysis shows a statistically significant negative trend in precipitation anomaly of 12.2 mm/decade (Table 6).

Given rising temperature anomalies are mainly attributed to increasing concentrations of greenhouse gases due to burning of fossil fuels and the manufacture of cement (IPCC, 2013), we have analyzed changes to greenhouse gas emissions data between 1960 and 2015. We detected a statistically significant change point in CO₂ emission data in 1985, such that CO₂ emissions increased from 78,660 Kt/yr between 1960 and 1985 to 337,701 Kt/yr between 1985 and 2015 (Fig. 5), because of increasing consumption of solid, liquid, and gas fuels and flaring after 1985. A trend analysis shows a statistically significant positive trend in CO₂ emissions of 94,340 Kt/decade (Table 6).

Other greenhouse gases produced by industrial processes are such as hydrofluorocarbons (HFC), perfluorocarbons (PFC), and sulfur hexafluoride (SF₆), as presented in Fig. 6. These greenhouse gases also show statistically significant change point in 1984, where the mean annual HFC, PFC, and SF₆ emissions increased dramatically from 884.4 Kt/yr between 1971 and 1984 to 2025 Kt/yr between 1984 and 2012, and an overall statistically significant positive trend of 488.5 Kt/decade. The warming effects of these greenhouse gases and LUC such as urbanization, deforestation and construction of dams in the study area had resulted in the consistent, observed positive temperature

Table 6

Change point and trend detection.

	Years	Pettitt test			Mann-Kendall test					
		t	P	trend	Tau	Sen's slope	P	trend	Mb	Ma
T anomaly	1900–2010	1968	<0.0001	Ha	0.434	0.024	<0.0001	+	−0.206	0.326
Precipitation anomaly	1948–2014	1967	0.0001	Ha	0.133	−1.22	<0.0001	−	7.9	−3.12
CO ₂ emissions (Kt)	1960–2015	1985	<0.0001	Ha	1	9434	<0.0001	+	78,660	337,701
Other greenhouse gas emissions HFC, PFC and SF ₆ (Kt)	1971–2012	1984	<0.0001	Ha	0.6	48.85	<0.0001	+	884.4	2025
Total greenhouse gas emissions (Kt of CO ₂ equivalent)	1971–2012	1991	<0.0001	Ha	0.94	7809	<0.0001	+	196,902	348,896

Table 7

Area measurements of land cover/use projection 2025, 2050, 2075, and 2100.

Code	Land cover/use class	2025		2050		2075		2100	
		Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)
1	Water bodies	63.800	0.484	58.900	0.447	50.102	0.380	43.669	0.331
2	Built up areas	2640.653	20.032	2732.886	20.732	2753.937	20.892	2790.300	21.168
3	Bare soil	6498.476	49.298	6164.481	46.765	6100.740	46.281	5970.401	45.292
4	Sparsely vegetated	1169.357	8.871	1182.924	8.974	1180.068	8.952	1189.728	9.025
5	Irrigated cropland	2161.152	16.395	2279.9475	17.296	2313.637	17.552	2400.4565	18.210
6	Forest and shrubland	648.5265	4.920	762.8256	5.787	783.4806	5.944	787.4091	5.973

trend since the mid-Twentieth Century. Fig. 7 shows the time series of total greenhouse gas emissions that include all anthropogenic sources, which show a statistically significant change point in 1991, with positive trend of 78,090 Kt/decade (Table 6).

From Fig. 8a that shows the historical and projected change in temperature anomalies between 1900 and 2100, it can be seen that significant warming trend started to occur in 1970s attributed to human activities such as industrial boom, deforestation, rapid urbanization and increase in greenhouse gas emissions. Future temperature anomalies in the study area simulated by global climate models of CMIP5 and IPSL-CM5A-LR under three climate scenarios (RCP4.5, RCP6.0 and RCP8.5) project a continuous warming trend between 2014 and 2100. Fig. 8b shows the time series of the average temperature anomaly simulated by all climate models between 1900 and 2100 with a statistically significant change point that occurred in 1999 and a projected warming trend of 0.19 °C/decade.

The warming trend in the study area varies spatially with the nature of land use. We compare the projected change with the projected LUC patterns over the study area. As a warming trend is expected to continue, especially in the mountains areas where the warming trend is projected at 0.55–0.83 °C/decade between 2014 and 2050. In south and eastern parts of the Jizzan Province, warming is projected at 0.55 °C/decade (Fig. 9b), where Ragab and Prudhomme (2002) projected that the temperature may increase by 1.5–2.5 °C (0.41–0.7 °C/decade) in 2050. By 2075, mountains areas and its surroundings are projected to experience an increase in the mean annual temperature by 4.2–5 °C, a warming trend of 1.25–1.38 °C/decade between 2050 and 2070, while the temperature of south and western parts of Jizzan province is projected to increase by 2.3 to 3.3 °C, a warming trend of 0.63–0.92 °C/decade between 2050 and 2075 (Fig. 9c).

The mean annual precipitation of Jizzan ranges spatially from 77 to 272 mm/year (Fig. 10a) with mountainous regions receiving the highest amount of 179–272 mm/year, followed by northeastern and northwestern regions with an annual rainfall ranging from 140 to 272 mm/year. As expected, high spatial variability of rainfall in Jizzan also means that Jizzan has high hydrologic variability (e.g., Jiang et al., 2014; Mwale et al., 2009). However, the annual rainfall of Jizzan projected to 2050 (Fig. 10b) is expected to decline by 6% in southeastern regions of Jizzan, and by 3% in northwestern, eastern, and southwestern regions which are occupied by built-up areas, crops, forest, and bare soil. The negative trend is projected to worsen from 2050 to 2075 (Fig. 10c), by as much as 8% in the mean annual rainfall in northwestern, eastern,

and southwestern regions. However, the negative trend is projected to be only 2% in both the southeastern and central regions.

4.3. Land use change prediction

The landuse of Jizzan is projected to increase in urbanization and irrigated cropland in 2025, 2050, 2075, and 2100 as presented in Table 7 and Fig. 11. The bare soil area is projected to decrease from 7020.1 km² in 2014 to 6498.4 km² in 2025, while water bodies areas are projected to decrease from 73.4 km² in 2014 to 63.8 km² in 2025. In contrast, urban areas are projected to increase from 2456.4 km² in 2014 to 2640.6 km² in 2025, and then to 2732.9 km² in 2050. Similarly, sparse vegetation, and forest and shrubland are projected to increase from 1120.3 km² and 548.1 km² in 2014 to 1169.3 km² and 648.5 km² in 2025, respectively. In addition, irrigated cropland is projected to substantially increase from 1963.6 km² in 2014 to 2161.2 km² in 2025. By 2050, irrigated cropland is also projected to expand from an area of 2161 km² in 2025 to 2279.0 km² in 2050, or a projected increase of 5% (Table 8). In contrast, bare soil is projected to decrease by 5%, sparse vegetative cover to decrease by 1%, but water bodies are projected to decrease significantly by almost 8% due to continued urbanization. For forest and shrubland, the model projected a 17% increase between 2025 and 2050. By 2075, the model projected urban areas, irrigated cropland, forest, and shrubland to increase by 0.8%, 1.5%, and 3%, respectively, but water bodies, bare soil, and sparsely vegetated land are projected to decline by 15%, 1%, and 0.2%, respectively. However, between 2075 and 2100, urban areas, irrigated cropland, forest and shrubland, and sparsely vegetated areas are projected to increase by 1%, 4%, 0.5%, and 1% respectively. In contrast, water bodies are projected to decrease by 13% of its area in 2075, a slight decrease is also projected in bare soil by 2% of its area in 2075 (Table 8).

Urbanization further exacerbated the climate change impact of rising greenhouse gases in the province, as warming trend became statistically significant after 1970, which happened to be the year urbanization began to exhibit increasing trend. Spatially, the annual temperature is projected to increase most significantly within urban areas and mountainous regions by 2050 and 2075. Mountainous areas are projected to be much warmer because the cooling effect of evapotranspiration is significantly reduced by deforestation, which were previously occupied by shrubland and forest reflects the impacts of deforestation in the warming trend.

Table 8

Expected gains and losses during projected period (2014–2100).

Code	Land cover/use class	2014–2025		2025–2050		2050–2075		2075–2100	
		Change (Km ²)	Change (%)	Change (Km ²)	Change (%)	Change (Km ²)	Change (%)	Change (Km ²)	Change (%)
1	Water bodies	9.562	13.034	4.900	7.680	8.798	14.937	6.433	12.840
2	Built up areas	–184.223	–7.500	–92.233	–3.493	–21.050	–0.770	–36.363	–1.320
3	Bare soil	521.648	7.431	333.995	5.140	63.741	1.034	130.339	2.136
4	Sparsely vegetated	–49.078	–4.381	–13.567	–1.160	2.856	0.241	–9.660	–0.819
5	Irrigated cropland	–197.469	–10.056	–118.7955	–5.497	–33.6895	–1.478	–86.8195	–3.753
6	Forest and shrubland	–100.44	–18.326	–114.2991	–17.624	–20.655	–2.708	–3.9285	–0.501

Where (–) gain, (+) loss.

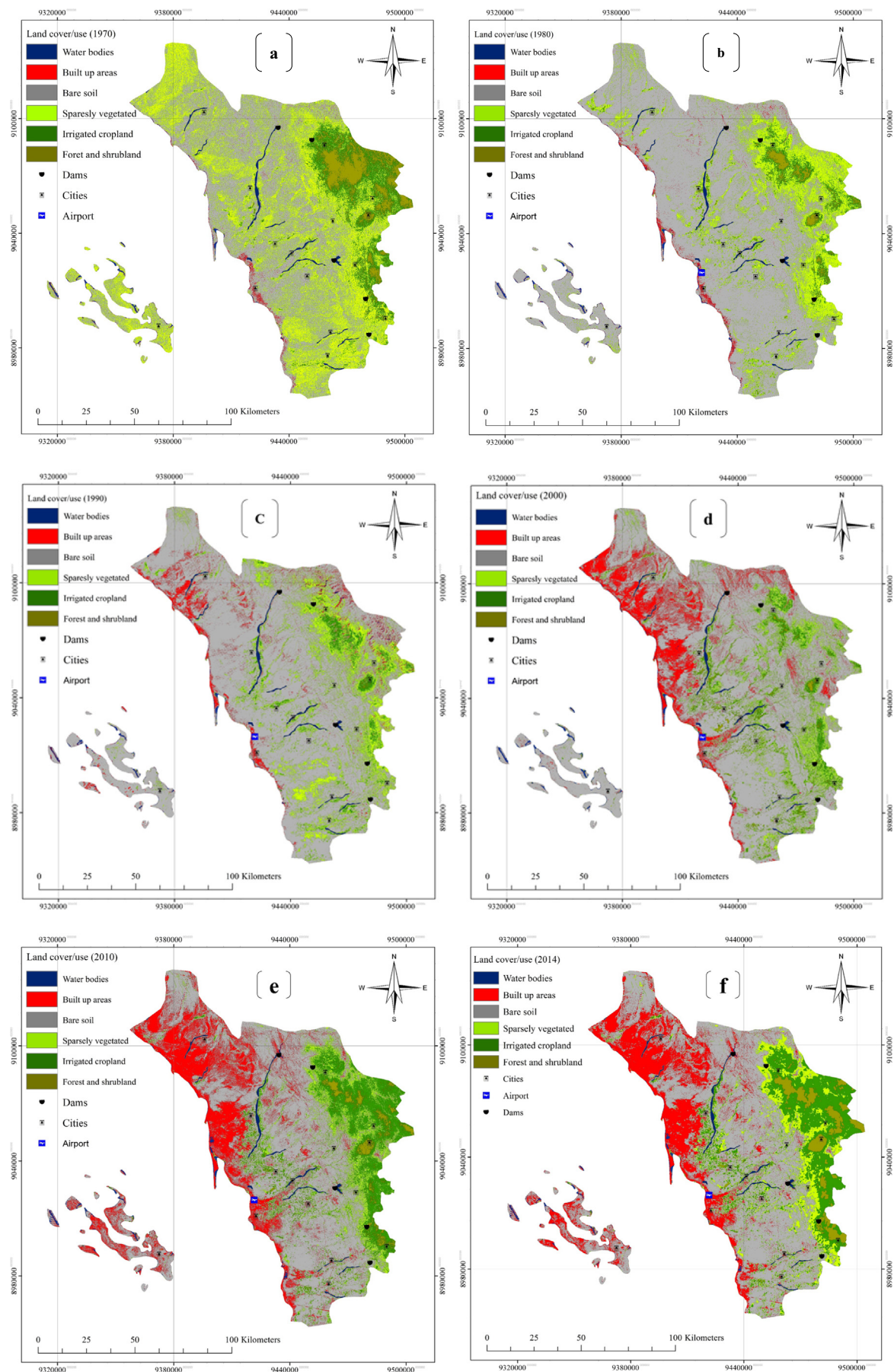


Fig. 2. Spatial distribution of land use a) 1970, b) 1980, c) 1990, d) 2000, e) 2010, and f) 2014.

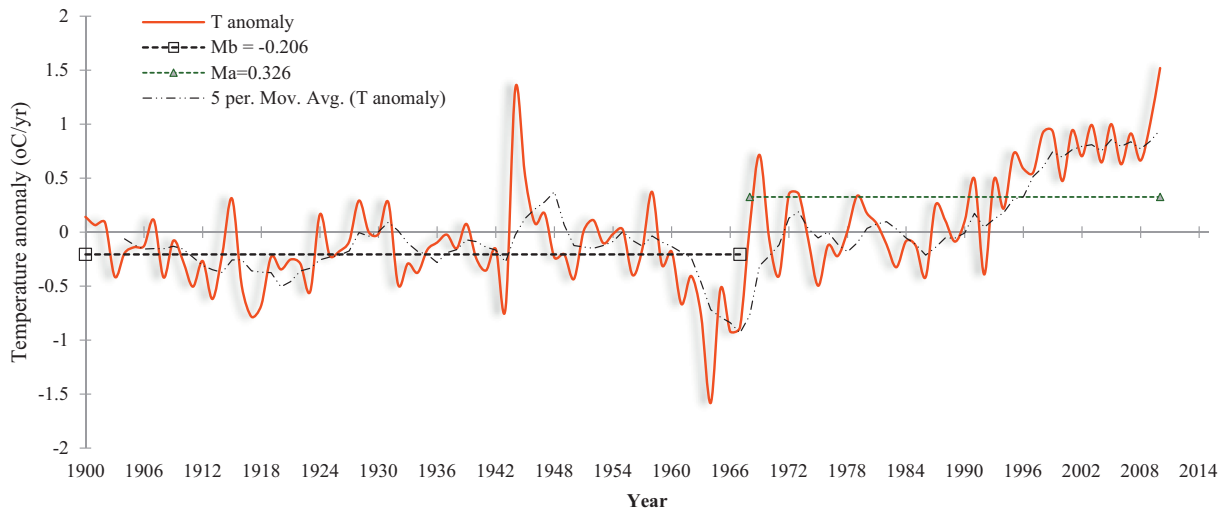


Fig. 3. Temperature anomaly and trend.

4.4. Impacts of land use change and climate change on Fauna and Flora

Results collected from the field survey and from the questionnaire reveal a strong agreement between our study and local residents, that increasing emissions of greenhouse gases and human activities have led to climate warming in the study area and a significant decline in its ecosystem services. For their survival, in the past 50 years, many wild animals had migrated to cities and villages in search of water, which may jeopardize human health and life. LUC due to urbanization of rural and mountainous areas have likely contributed to the decline in annual rainfall at about 12.2 mm/decade and the biodiversity of these areas. For example, the Arabian Baboon (*Papio hamadryas*) populations were partially controlled by their natural predators, leopards (*Panthera pardus*) and striped hyenas (*Hyaena hyaena*) but these predators have been hunted to extinction in these regions which have the habitats needed by the predators. On the other hand, these areas are facing serious threats of loosing of their habitats due to major agricultural expansion and irrigation projects (Biquand et al., 1992 and Winney et al., 2004). In other words, aforementioned human activities have led to significant degradation of the environment, impacts on the Afrotropical biodiversity of the region, coastal marine ecosystems, fragmentation and destruction of habitats.

The draining of coastal areas for tourism and ornamental projects have caused marked declines of many species of mammals and birds that rely on this habitat for food (Nasser et al., 2015), either being eliminated or have migrated to other areas. Wading shorebirds, for example, have lost their niche due to the urbanization of most coastal areas in the Jizzan Province. The Farasan Islands, the first conservation protected area in Saudi Arabia, is home to the endangered Arabian gazelle, *Gazella arabica* (Lichtenstein), and serves as a rest area for many migratory bird in their migration route between Europe, northern Asia, and Africa. Farasan Ghazal is a distinctive subspecies of well-known Arabic gazelle, native to the islands. For the last fifty years, this island supported large populations of Farasan Ghazal because of low human impacts and consistent high annual rainfall (Thouless, 1991; Thouless and Al Bassri, 1991). Unfortunately, overhunting and a gradual decrease in the annual rainfall has led to a major collapse of this animal's population.

LUC has probably been a stronger driver of twentieth-century changes in wild plants and animals than climate change (Parmesan and Yohe, 2003). LUC pattern showed a large decline in flora and natural vegetation cover in the study area partly because rainwater, the only source of water that supports fauna and flora, has been decreasing in recent years. Moreover, significant deforestation, rapid urbanization, increased greenhouse gases have direct effects in plant distributions, as

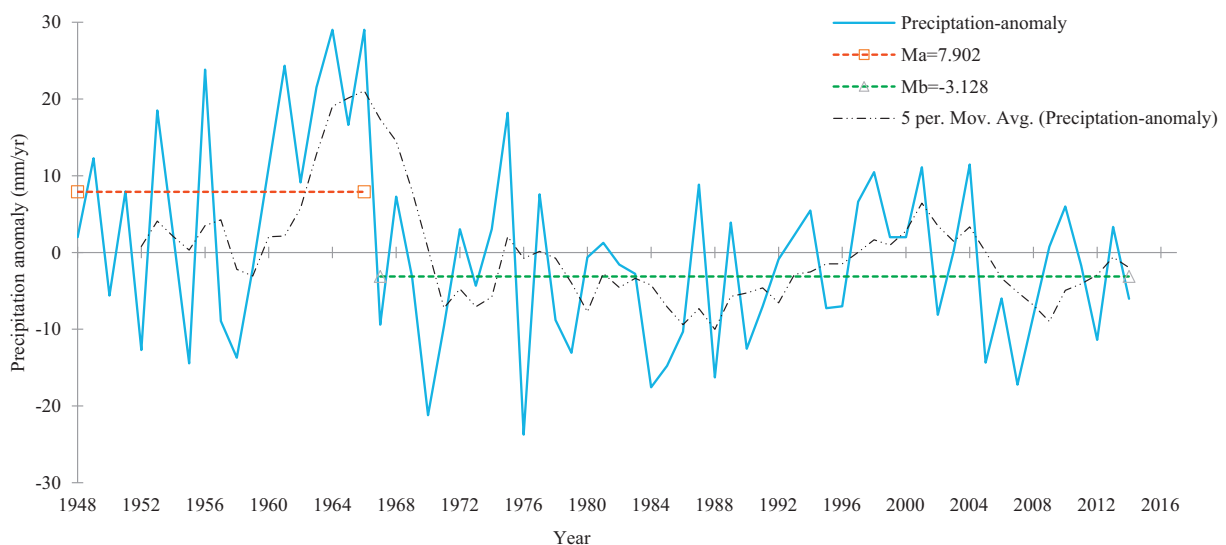


Fig. 4. Precipitation anomaly and trend.

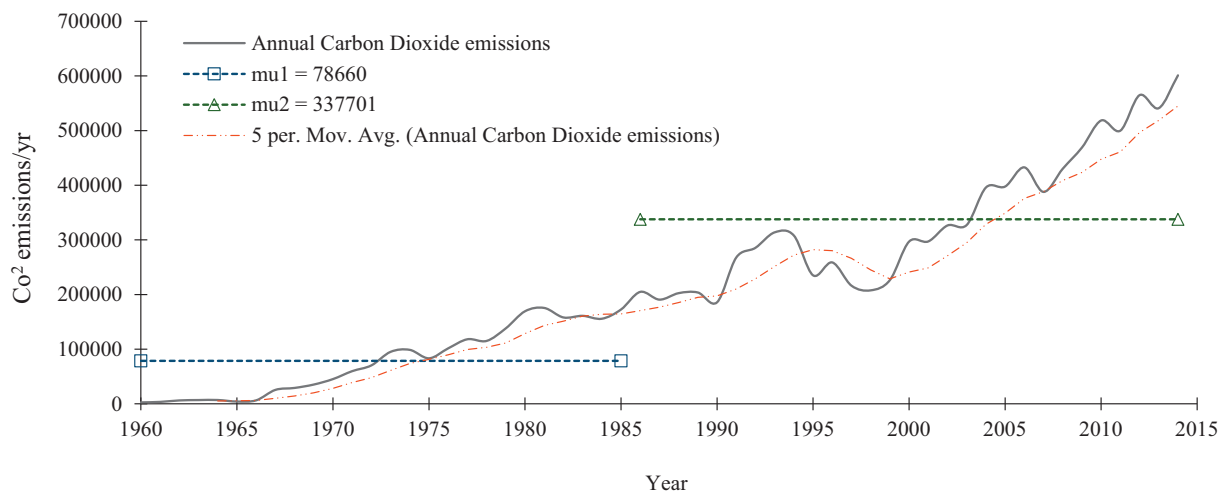


Fig. 5. Carbon dioxide emissions time series and trend.

discussed before. Another impact of climate change is more ET loss, which in turn decrease the soil moisture and affecting plant growth (Narasimhan and Srinivasan, 2005).

The annual ET time series estimated from local climatic factors for the study area over 1950–2014 (Fig. 12) has a statistically significant change point in 1975 with positive trend of 5.5 mm/decade. The rising trend in ET would increase plant stress and enhance drought conditions. The annual ET is also projected to increase significantly from 1500 mm/yr in 2014 to about 1850 mm/yr in 2100. If precipitation surplus, the net flux of water from the atmosphere to the soil surface is positive, it means wet soil; if it is negative, we will expect dry soil (Swenson and Wahr, 2006). Fig. 13 shows a significant increase in water losses from the soil profile over time which means dry soil and it is expected to continue according to our future projection. Therefore, under diminishing soil moisture, warming trend and rapid urbanization, we expect the flora and natural vegetation cover in the study area to continue to decline in the 21st Century.

5. Conclusions and recommendations

We investigated the impact of anthropogenic climate change and human activities such as LUC on the environment and ecosystem

services in the Jizzan Province, Arabia. First, we used earth observation data of the Landsat satellite to derive historical, 1970–2014, land use maps of Jizzan. Next, we used a Markov-CA model to project the dynamics of its LUC pattern over 2014–2100 in response to human activities and their impacts on the study area's climate, environment, and water resources. We applied Pettit's and Mann-Kendall tests to detect change points and to estimate trends of temperature data of 1900–2010 and precipitation data of 1948–2014 and their anomalies, respectively. We have also detected change points and estimated trends of data of CO₂ and several rare gases emitted between 1960 and 2015. Climate scenarios (RCP4.5, RCP6.0 and RCP8.5) of the study area projected by climate models of CMIP5 were used to project future warming in the study area between 2014 and 2100.

Urbanization and LUC has significant impact the ecosystems, biodiversity and natural habitats of the Jizzan province. In 1970s, human impacts were minimal. However, following the construction of rain-harvesting dams which capture most surface runoff, and with urban expansion at about 53.4 km² yr⁻¹ which extended into coastal regions, areas of forest, shrubland, sparse vegetative cover, bare soil and water bodies declined markedly over 1990–2014. Likely due to climate change impact and urbanization, a statistically significant change point was detected in the monthly temperature data of jizzan in 1968 and a warming

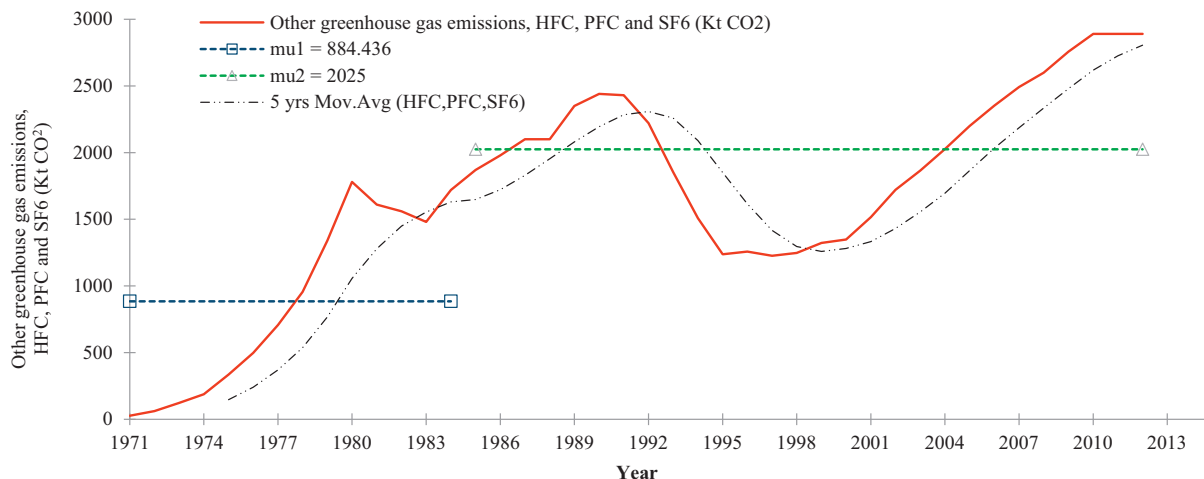


Fig. 6. Other greenhouse gas emissions, HFC, PFC, and SF6.

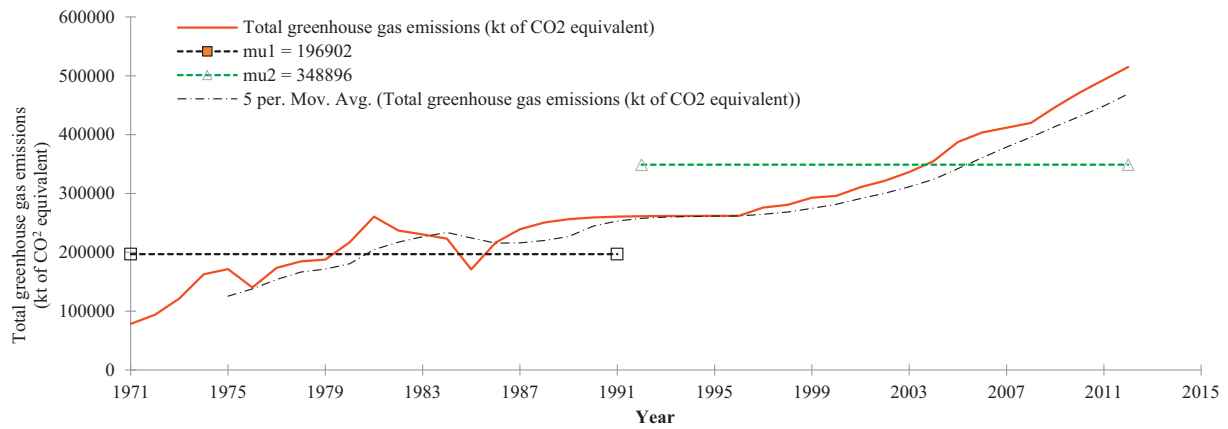


Fig. 7. Total greenhouse gas emissions including all anthropogenic sources.

trend of 0.24°C per decade after 1970. The precipitation data also had a statistically significant change point in 1967, but a negative trend of 12.2 mm/decade . Observed changes in the hydro-climatology of Jizzan are

likely associated with significant LUC, such as urbanization and agricultural development (irrigated croplands) at the expense of vegetative cover, forest, shrubland, and sparse vegetative cover since 1970s.

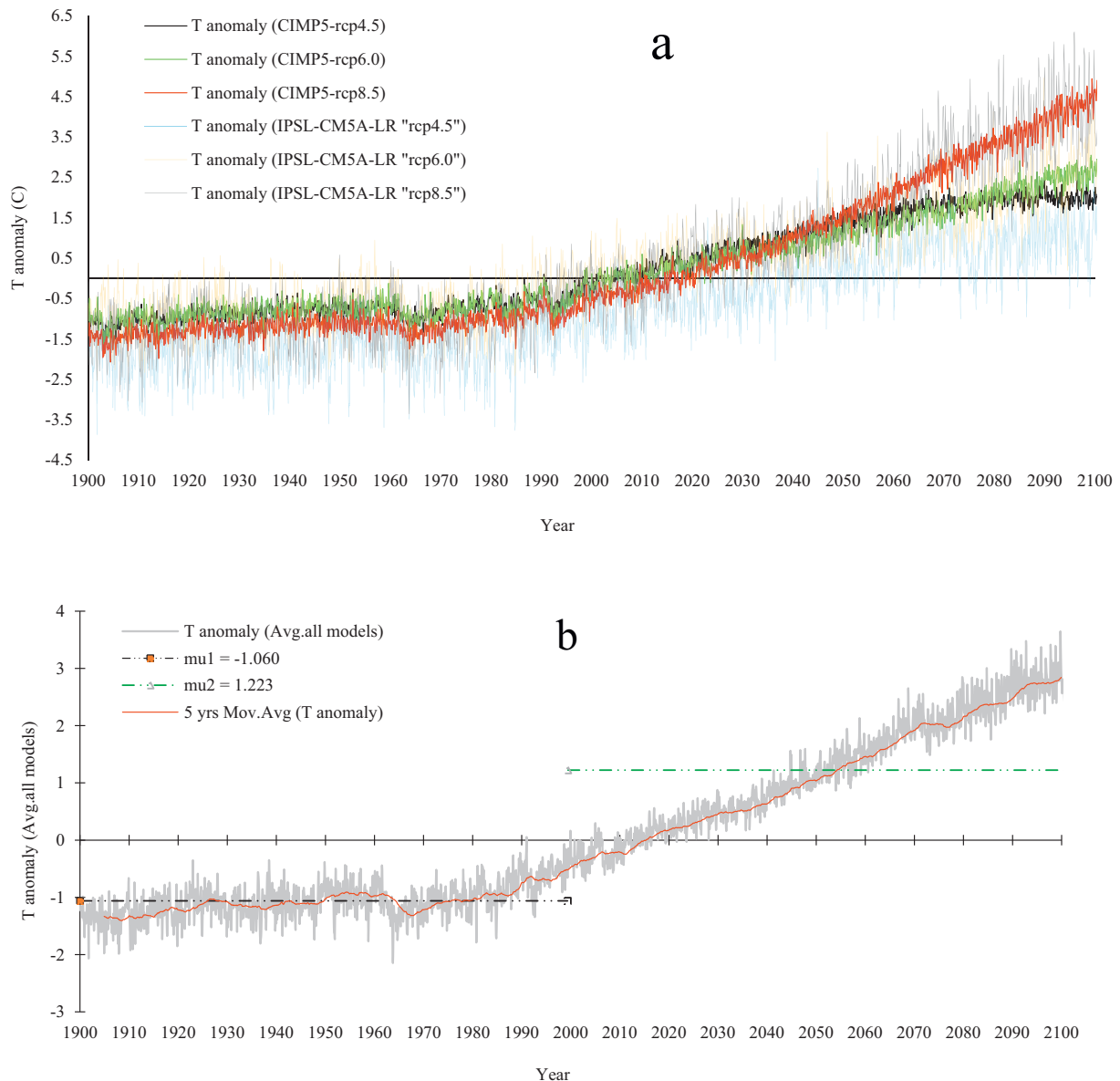


Fig. 8. Projection of temperature anomaly (a) average temperature anomaly trend (b).

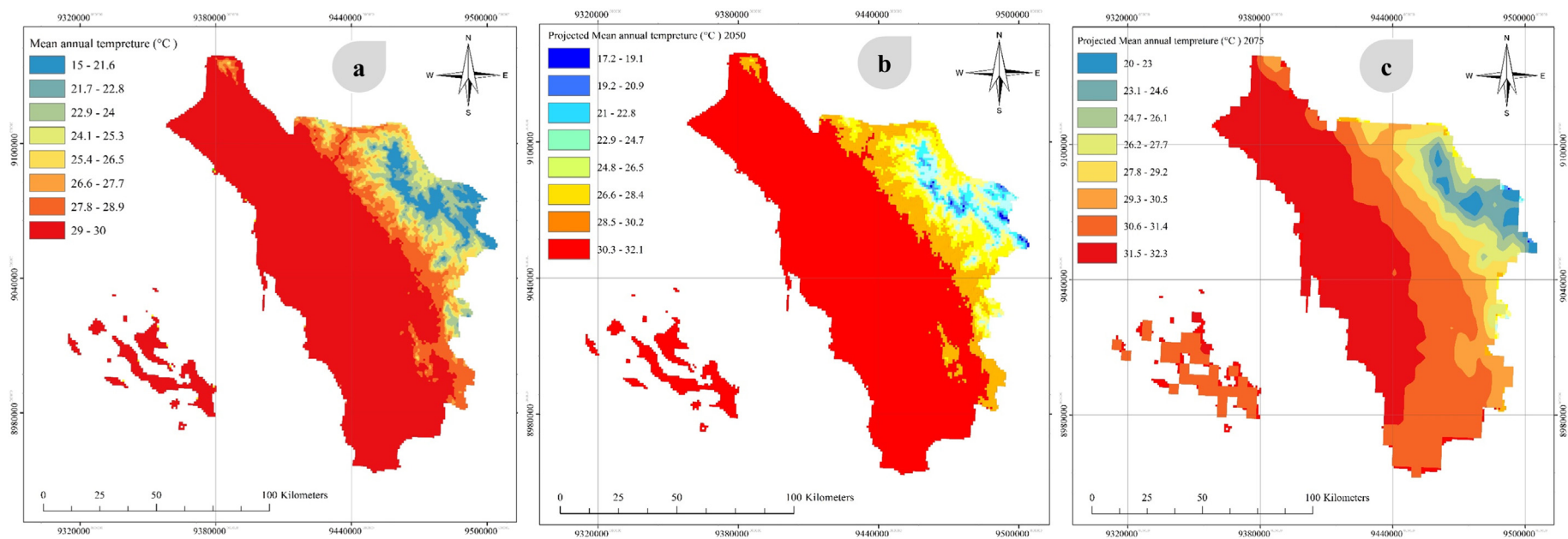


Fig. 9. Average annual temperature (a) and future projection in 2050 (b) future projection in 2075 (c).

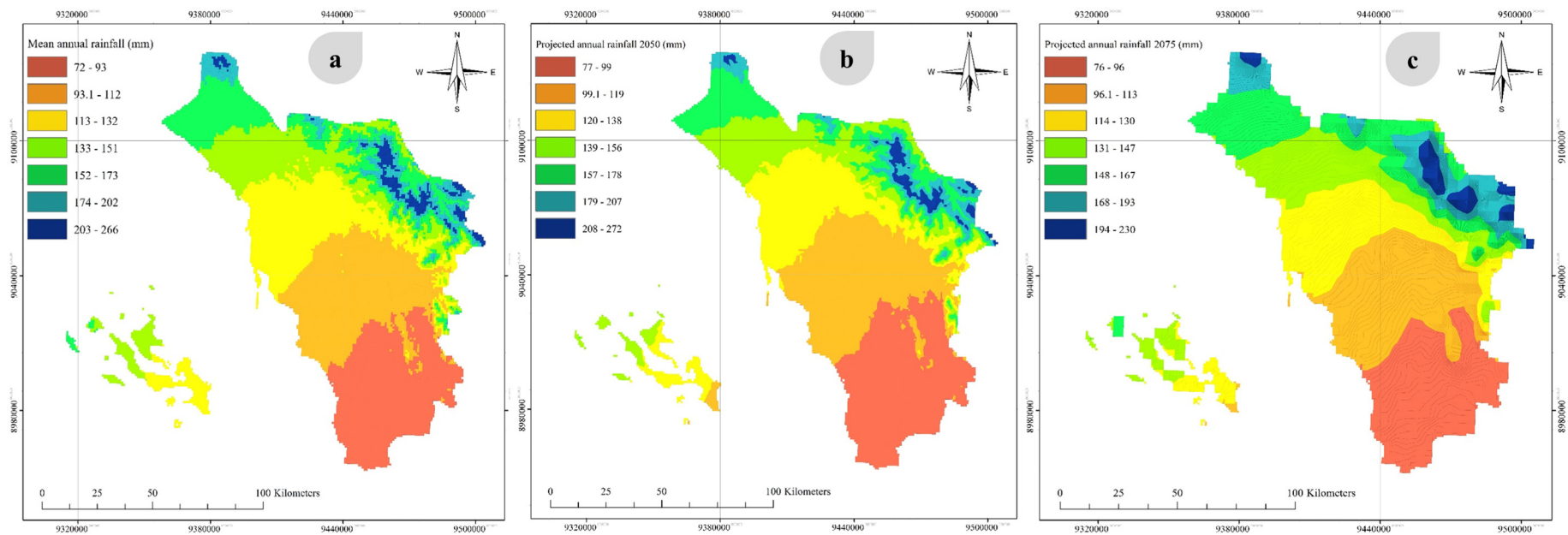


Fig. 10. Average annual precipitation (a) and future projection in 2050 (b) future projection in 2075 (c).

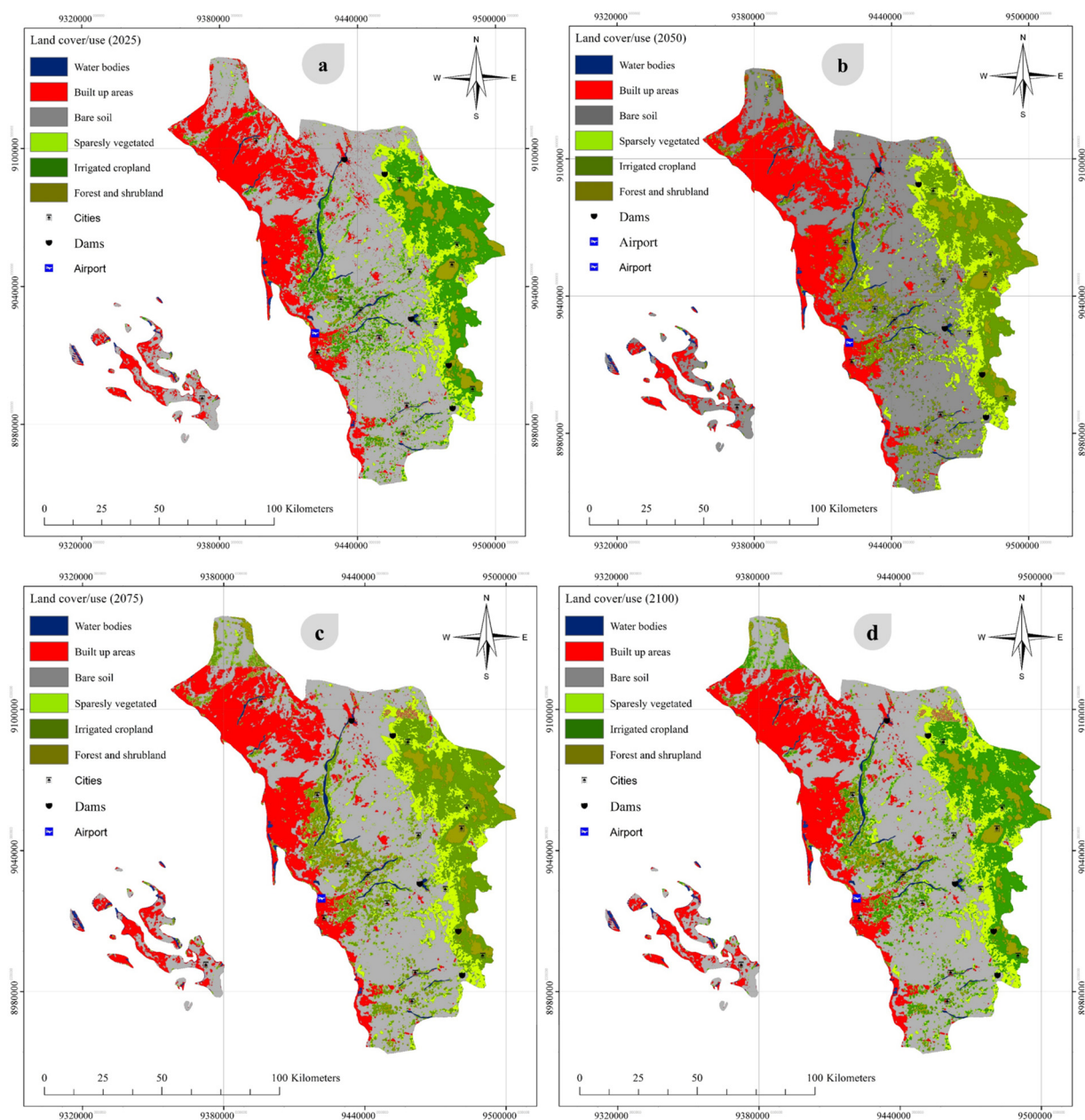


Fig. 11. Spatial distribution of projected LULC a) 2025, b) 2050, c) 2075, d) 2100.

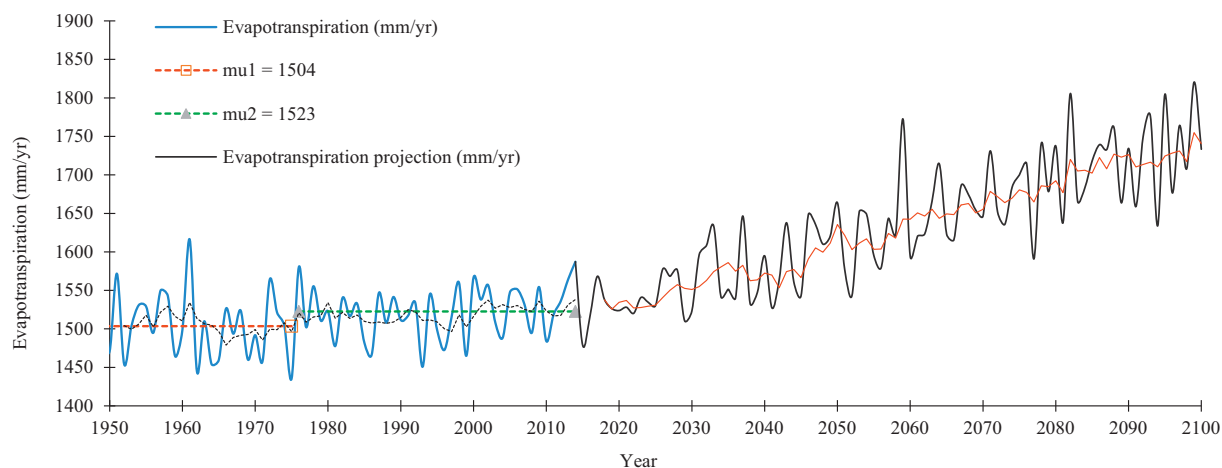


Fig. 12. Annual evapotranspiration trend and future projection.

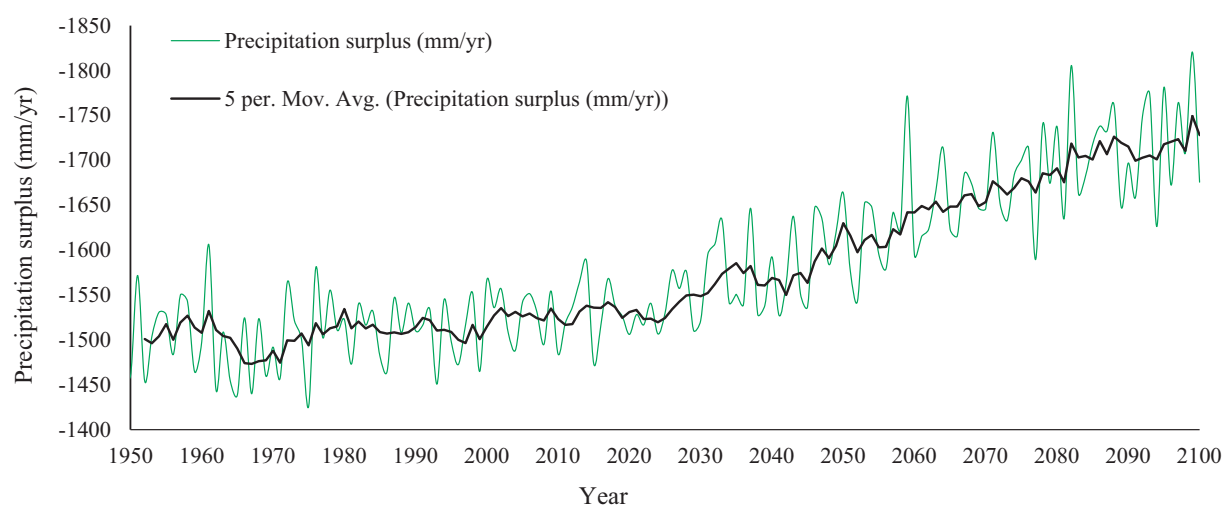


Fig. 13. Annual precipitation surplus and future projection.

A statistically significant change point was detected in CO₂ emissions data in 1985 and statistically significant positive trend of 94,340 Kt/decade. Other anthropogenic greenhouse gases mainly due to industrial processes also have a statistically significant positive trend of 488.5 Kt/decade. On a whole, total greenhouse gas emissions including all anthropogenic sources have been increasing at a statistically significant trend of 78,090 Kt/decade after 1991. Therefore, it is very likely that long-term increasing emission of greenhouse gases, and aforementioned human activities have resulted in warming trends observed in the study area and globally. Future projection of temperature anomaly between 1900 and 2100 showed a statistically significant future warming trend of 0.19 °C/decade after 1999.

The spatial distribution of the projected annual temperature in 2050 and 2075, also shows that the highest increase in temperature is within urban areas and the mountains regions. The increase in the warming trend in the mountains areas which were previously occupied by shrubland and forest reflects the impacts of deforestation in the warming trend. The warming trend in mountains regions is estimated at 0.55–0.83 °C/decade between 2014 and 2050, and at 0.55 °C/decade in south and eastern parts of Jizzan Province. Precipitation is projected to continue declining while LUC such as urbanization and irrigated cropland are projected to continue towards the end of the 21st Century.

In conclusion, to reduce the impacts of climate change and LUC, conservation plans for the Jizzan Province are essential to mitigate the significant impact human activities and global warming on the environment and ecosystem services of the study area in the 21st Century.

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